



Reliability analysis and optimum maintenance of coastal flood defences using probabilistic deterioration modelling

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ABSTRACT

This paper presents a method for time-dependent reliability analysis, future performance predictions and optimum maintenance strategy of coastal flood defences such as earth sea dykes subjected to changing operation conditions. The reliability analysis takes into account both the changes of hydraulic variables such as water level and wave height due to climate change and the deterioration of structural capacities such as crest freeboard loss and soil seepage length degradation over time. A probabilistic time-dependent semi-Markov process is adopted for estimating the transition probabilities on the basis of available field data through routine inspections and expert judgements. Limit state equations are established for evaluating time-dependent probability of failures associated with wave overtopping through the flood defence crest and piping in the underlying water conductive soils. A multi-objective optimisation method is then employed to find optimum solution space for asset inspection and maintenance by minimising both costs for inspection and annual risk of structural failures. The results for a typical earth sea dyke at Thames Estuary show that the probability of failures associated with wave overtopping and soil piping will increase significantly over time, thus appropriate maintenance strategy is required to reduce the risk caused by changing operating conditions.

1. Introduction

Coastal flood defences such as earth sea dykes are the first lines to protect low-lying areas and valuable assets against risks posed by flooding, coastal erosion and landslides. It is thus necessary to manage effectively the risks and to avoid casualties and asset damage with limited resources available. Coastal defences are often constructed in harsh and changeable operating environments, thus it is difficult to assess accurately the future risks caused by structural failures. The future hydraulic variables such as water level and wave height acting on the coastal defences can be affected by sea level rise due to climate change. The rise of sea level causes the increase in local significant wave height and the reduction in structural capacities by decreasing the crest freeboard. This leads to increasing wave overtopping discharge through the crest of coastal flood defences. In the meantime, the existing coastal defences deteriorate with time such as crest level loss and seepage length degradation in water conductive soils, leading to further decrease in structural reliability and safety. Therefore, time-dependent reliability analysis is necessary to assess the risk of coastal flood defences under double effect of changing hydraulic conditions and deteriorating structural resistance. This will provide a quantitative basis for

analysing accurately risks and optimising inspection and maintenance strategy of the coastal flood defences.

The impacts of climate change on the major hydraulic variables of coastal flood defences such as still water level and significant wave height are investigated in many studies [1–3]. In the UK Climate Projections (UKCP) report [3], the projections of sea level rise for various regions in the UK due to climate change over the 21st century are recommended, subject to various emission scenarios. The range with the 5th to 95th percentile confidence intervals of absolute sea level rise around the UK before consideration of vertical land movements is projected to be between 12 and 76 cm by 2095, depending on emission scenarios. Recently, the influence of the change in sea water level and significant wave height on the performance of coastal defences has been investigated. Chini and Stansby studied the effect of climate change to predict overtopping discharge by utilising a joint probability method for sea water level and significant wave height [4]. Sierra et al. investigated the influence of sea level rise under three different scenarios on wave overtopping discharge to assess the vulnerability of port breakwaters [5]. These results show that wave overtopping discharge rates will increase in the future due to more severe hydraulic conditions caused by climate change.

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Predicting asset deterioration over time is another challenge in the management of coastal flood defences, since deterioration leads to decrease in structural resistance against various failure mechanisms including wave overtopping. In order to model accurately the asset deterioration process, stochastic deterioration models have been proposed and applied in various civil engineering systems, such as bridges, pavement, pipeline, and wastewater systems [6–8]. Baik et al. proposed a Markov chain model to predict the future performance deterioration of wastewater systems using available inspected data [9]. Saydam et al. investigated the deterioration process of bridge components by using the homogeneous Markov transition probabilities between the condition states [10]. Kleiner proposed a semi-Markov process with an assumed probability distribution of waiting times for large infrastructure assets [11]. Mishalani and Madanet proposed a state-based Markov process with time-dependent transition probabilities using stochastic duration model in order to predict the future conditions of infrastructure systems [12]. These time-dependent stochastic Markov processes consider the possible time-dependency for the deterioration process in reality and overcome some limitations in homogeneous transition processes.

Recently, research has been carried out on future performance predictions and optimum maintenance strategies of coastal flood defences, including stochastic deterioration modelling, time-dependent reliability analysis and reliability-based maintenance strategy [13–15]. Buijs et al. described practical time-dependent reliability models for components in flood defence systems to represent flood defence deterioration [16]. These statistic models can represent the time-dependence of flood defences in data scarce situations, and provide a basis for evaluating the future performance of the structures. Bachemann et al. proposed a probabilistic failure analysis method where a two dimensional flood spreading simulation is utilised in order to evaluate the flood impacts and consequences [17]. Chen et al. proposed a method for optimising the expected maintenance cost and inspection time interval on the basis of time-dependent reliability analysis. The proposed method attempts to find the balance between the costs for maintenance and the risk of structural failure of deteriorating sea defences for better reliability-based decision making [18–19]. However, most of these studies are limited to the asset deterioration modelling and performance assessment of flood defences, and limited information is available about optimum maintenance strategy that depends on the time-dependent probability of failures of existing coastal flood defences affected by both changing hydraulic conditions and structural resistance deterioration over time.

This paper proposes a method for assessing time-dependent reliability of coastal flood defences such as earth sea dykes subjected to both changing hydraulic conditions and deteriorating structural capacity over time. The changes of local hydraulic variables such as water level and depth-limited significant wave height due to sea level rise are investigated. The deterioration of the earth dykes such as the dyke crest level loss and seepage length degradation is modelled using a probabilistic time-dependent Markov process. The semi-Markov transition probabilities are then estimated based on available field data through

routine inspections and expert judgements by assuming Weibull distributed waiting times. On the basis of the changing hydraulic variables and deteriorating structural capacity, time-dependent reliability analysis is undertaken with respect to wave overtopping failure and soil piping failure, which is then used for optimising inspection and maintenance strategy through a multi-objective optimisation method. Finally, a numerical example for a typical earth sea dyke at Thames Estuary is employed to demonstrate the applicability of the proposed method.

2. Changing hydraulic conditions

Hydraulic variables such as water level and wave height may change with time due to climate change in the future. The changing hydraulic variables can increase the risk to existing flood defences, thus extreme values and hydraulic loads on the defences need to be investigated for probabilistic risk assessment.

2.1. Extreme value analysis

Several techniques are available to perform extreme value analysis. A generalised extreme value (GEV) distribution can be utilised to fit the block maxima of each hydraulic variable (e.g. water level and wave height), as described in [20], since the GEV distribution can model the largest value among a large set of independent, identically distributed random values representing measurements. For the cases of coastal flood defences, the GEV distribution is the limit distribution of properly normalised maxima of a sequence of random variables such as sea level and wave height. Hence, the distribution is often used as an approximation to model the block maxima such as annual maxima for sequences of random variables. The cumulative density function (CDF) for the GEV distribution is given here as

$$F(x; \mu, \sigma, \kappa) = \exp \left[- \left\{ 1 - \kappa \left(\frac{x - \mu}{\sigma} \right) \right\}^{1/\kappa} \right] \quad (1)$$

where $\kappa \neq 0$, σ and μ are shape, scale and location parameters, respectively, which can be estimated using the maximum likelihood estimation methods [20]. Here, the return period is defined as the average period between occurrences of an unusually high value of a variable, and is expressed as the inverse of the probability of the variable exceeding the return level. For the quantile X_{T_r} , the return period T_r is written as

$$T_r = \frac{1}{1 - F(X_{T_r})} \quad (2)$$

In this study, a typical earth sea dyke, as shown in Fig. 1, is adopted for risk analysis due to changing hydraulic conditions and deteriorating structural capacities. This dyke section is simplified from the earth embankment along Allhallows-on-Sea at Thames Estuary, as described in [21]. The sea level and wave height measurements for the coastal flood defence are based on data for 40 years (1960–2000) from MAWS network and tide gauges at Thames Estuary available through Marine

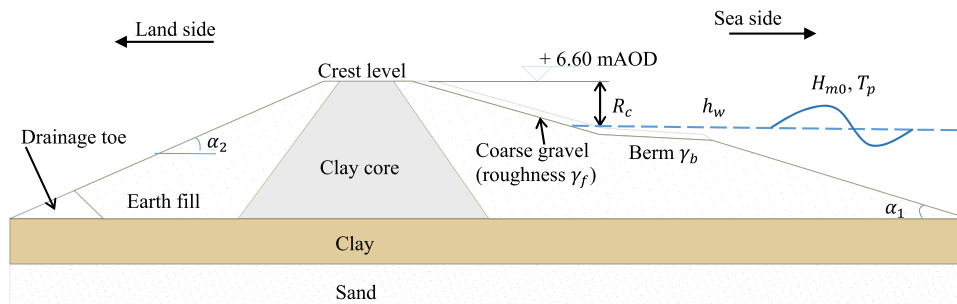


Fig. 1. Sketch of a typical earth sea dyke section at Thames Estuary.

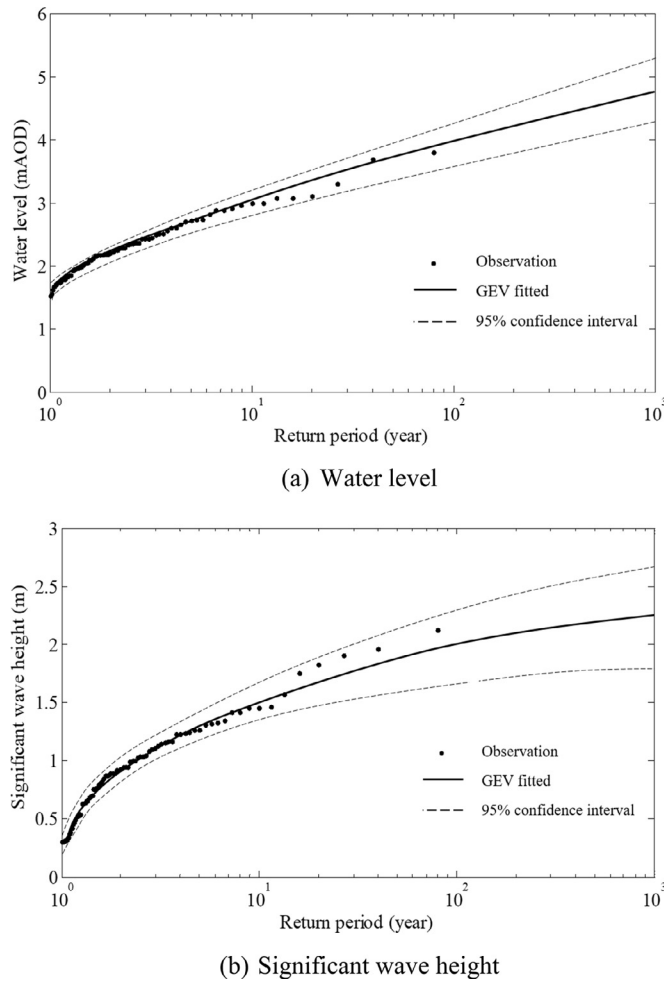


Fig. 2. Return periods of extreme water levels and wave heights with 95% confidence intervals at the present condition.

Processes and Climate report [22]. The annual maxima are used to model the frequency distribution of the extreme values of sea level and wave height. The extreme sea level and wave height distributions at the estuary are calculated using the GEV distribution fitted to annual maxima. Fig. 2 shows the results for the return periods with 95% confidence intervals for sea level and significant wave height at the present day (year 2000). The values of water level and significant wave height at the 1000-year return period are estimated as 4.81 mAOD and 2.23 m, respectively. These results of extreme values for water level and wave height are consistent with those estimated in [21].

2.2. Water level rise

Research shows that sea level will rise due to climate change, depending on greenhouse gas emissions and climate system sensitivity [1]. According to the UKCP report [3], the central estimates of relative sea level rise with respect to 1990 at the location of London by 2095 are 0.531 m or 0.52 cm/year in average for high emission scenario, 0.444 m or 0.44 cm/year in average for medium emission scenario, and 0.373 m or 0.37 cm/year in average for low emission scenario, respectively. As a result, the local water depth $h(t)$ at the toe of the earth sea dyke increases with time t due to sea level rise $\Delta h(t)$, expressed here as

$$h(t) = h(0) + \Delta h(t) \quad (3)$$

where $h(0)$ is the initial water depth at the assumed present day.

2.3. Local wave height

Sea level rise will increase the wave attack on coastal flood defences, if the wave heights are depth-limited. As reported by Sayers et al. [23], rising sea level is the most significant factor affecting loading on coastal defences, due to the depth limited nature of the wave conditions along much of the coast of England. Coastal flood defences with lower toe levels on the seaward side will experience more severe incident wave conditions since the depth-limited significant wave height increases due to rising sea level. The depth-limited significant wave height is related to many factors including still water level at the toe of the sea defence. From the energy decay numerical model for uniform foreshore slope by Van der Meer [24], the depth-limited significant wave height H_{m0} can be estimated from hydraulic variables including local relative water depth $h_l(t)$, deep-water wave steepness S_{op} and foreshore slope. The local relative water depth $h_l(t)$ is defined as

$$h_l(t) = \frac{h(t)}{L_{op}} \quad (4)$$

where peak wave length $L_{op} = gT_p^2/2\pi$ is related to peak wave period T_p , g is the acceleration due to gravity. The change in wave periods due to climate change is negligible [2] and will not be considered in this study. The deep-water wave steepness S_{op} is defined as deep-water significant wave height H_{so} over peak wave length L_{op} , given here as

$$S_{op} = \frac{H_{so}}{L_{op}} \quad (5)$$

Thus, the depth-limited significant wave height due to sea level rise over time is estimated when the wave parameters as well as the deep-water significant wave height are available. The details for estimating the depth-limited significant wave height are described in Van der Meer [24].

In this study, sea level rise over the 21st century for the locations around London under medium emission scenario is considered. Sensitivity increases of 0.11 m for storm surges and 0.35 m for changes in offshore wave heights by year 2075 are also considered. Fig. 3 shows the rising water level at the 1000-year return period at the toe of the dyke due to sea level rise, where a total water level rise of 0.36 m is predicted after 75 years from the present day for the central estimates, with values of 0.21 m and 0.54 m for the 5th and 95th percentile confidence levels, respectively. The predicted results for local depth-limited significant wave height related to rising sea level are also provided, where the foreshore slope of 1:30 is assumed, together with the sensitivity increases in storm surge and offshore wave height. It is found that the local significant wave height increases approximately 15% in 75 years from the present day for the central estimate, with increases of approximately 11% and 20% for the 5th and 95th percentile confidence levels, respectively.

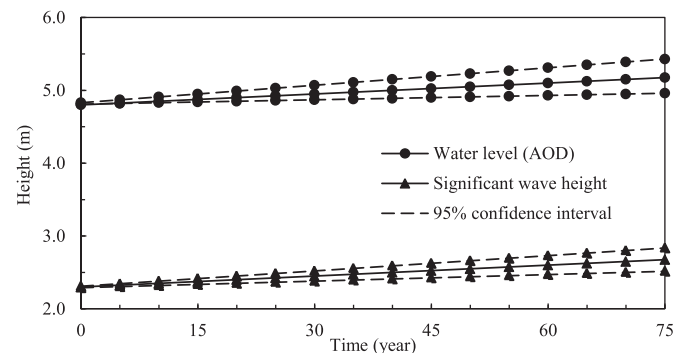


Fig. 3. Water level and local significant wave height from the present day at the 1000-year return period due to sea level rise with 95% confidence intervals.

3. Probabilistic deterioration modelling

Coastal flood defences deteriorate with time such as reducing dyke crest level and weakening soil strength, leading to decrease in structural reliability and increase in risk of structural failures. In order to predict accurately future performance of coastal flood defences, probabilistic approaches are needed for stochastic modelling of flood defence deterioration over time.

3.1. Asset condition inspection

Routine inspections of flood defences provide essential information about the assets' performance level. For proper asset inspections, an assessment manual is often required to provide a standardised framework for assessing structural condition and assisting decision making in management of flood defences, such as the Condition Assessment Manual by UK Environment Agency (EA) [25]. In the EA manual, five condition rates, ranging from "very good" to "very poor", are defined with specific descriptions to report structural conditions according to flood defence performance level. The condition grading of flood defence assets is indicated by using numeric values of 1 to 5. In this grading system, Condition State 1 (CS1) denotes the best condition where there even may be presents of superficial damage, while Condition State 5 (CS5) represents the worst condition where the asset is no longer able to perform its function at even a reduced level.

In general, various levels of inspections are included in operation and maintenance regulations. There are typically three main types of asset inspection strategy in practice [26], i.e. Tier 1: the default level, routine inspection; Tier 2: more detailed level, non-intrusive inspections; and Tier 3: highly detailed level, intrusive inspections. A Tier 1 inspection is routine asset inspection, and is the lowest level of monitoring using traditional methods such as visual inspection. Tier 2 and Tier 3 inspection strategy seeks more detailed information than that routinely collected in Tier 1 strategy, and is carried out by appropriate experts. The type of inspection adopted in practice depends on the timing and the regulatory framework by the asset manager. Regular inspections should be performed to provide a record of progressive problems, so that patterns can be identified and the need for intervention and maintenance is determined.

In order to improve the accuracy of asset condition assessment, quantitative assessment methods are proposed on the basis of inspection strategy, expert judgment and simplified performance level [27]. These methods attempt to find accurate linkage between structural damage and the relevant failure modes, such as wave overtopping failure due to dyke crest settlement and soil piping failure due to seepage length reduction. Table 1 gives the descriptions and dimensions of earth dyke crest level damage for different condition grades. Table 2 summarises the descriptions and magnitudes of seepage length loss in water conductive soils for various condition grades.

To quantify the extent of deterioration with time, a series of asset deterioration curves for different types of coastal and fluvial flood defences are proposed by using the historical observations and expert judgments [26,28]. The deterioration curves give information about the residual life of an asset with respect to its condition grade and deterioration rate, as shown in Fig. 4 for a typical sea dyke. For the fast deterioration rate, the coarse gravel on the surface dominates

deterioration. For the slowest estimate, deterioration is driven by the material. These curves are based on the condition grades defined in the EA condition grading system, and they take into account characteristics related to environment, asset age, material type and construction quality. The curves are developed on the basis of real data and information relating to the deterioration process of a specific flood defence asset with different rates. Condition grade deterioration curves offer many advantages, such as providing a standardised approach to assess the deterioration of flood defence assets, quantifying the residual life of the assets for different condition grades with and without maintenance, and allowing the user to evaluate their deterioration over time.

The information on deterioration rates of flood defence assets is useful for asset management. However, the asset performance often deteriorates with uncertainties, due to the nature of uncertain operating environments and material properties. Therefore, it is necessary to translate the deterministic deterioration rates into probabilistic deterioration models, so that the probabilistic asset deterioration modelling can be used for undertaking time-dependent reliability analysis and quantitative risk assessment.

3.2. Semi-Markov deterioration modelling

The Markov process model, as a typical state-based model, is adopted here for flood defence deterioration modelling, since this model can deal with the deterioration with uncertainties and overcome the limitations of deterioration curves. Let the discrete time Markov property s_t represent the state of an asset at time t ($t \geq 0$). For any time steps $\{1, 2, \dots, t\}$, the conditional distribution of the parameter s_t for given values of $\{s_1, \dots, s_{t-1}\}$ depends only on the last time step state s_{t-1} . A Markov chain is then determined by a transition probability function, which is the conditional probability of a transition from state i to state j during a given time period [29], expressed here as

$$p_{ij} = \Pr(s_t = j | s_{t-1} = i), \text{ where } i, j = 1, 2, \dots, M \quad (6)$$

in which M is the number of possible condition states, and $M = 5$ for the case of EA asset assessment method. The general form of Markov transition probability matrix $\mathbf{P}$ is then written as

$$\mathbf{P} = \{p_{ij}\}, \text{ where } p_{ij} \geq 0 \text{ and } \sum_{j=1}^M p_{ij} = 1 \quad (7)$$

If no rehabilitation or repair work is undertaken, the flood defence assets will gradually deteriorate and hence their corresponding condition state will either upgrade to a higher number or remain unchanged during the inspection period. Hence, the transition probabilities p_{ij} in Eq. (7) are null for $i > j$ where i and j are aforementioned condition states. In general, the unidirectional transition of condition rating would not be upgraded by more than one state within one unit period, and hence the probabilities of upgrading to more than one state are zero [9,11]. The transition probability matrix $\mathbf{P}$ now becomes an upper triangular diagonal matrix, expressed here as

Table 1
Crest height loss in earth dykes and the assumed distribution for each condition grade.

Condition grade (CG)	Damage description	Loss of crest height (m)	Distribution assumed
CG1	Cosmetic defects, very good surface protection, slight wearing of crest elevation	0.00–0.05	Lognormal
CG2	Slight rutting, good embankment surface protection, slight wearing of crest elevation	0.05–0.10	Normal
CG3	Minor rutting, fair embankment surface protection, minor wearing of crest elevation	0.10–0.20	Normal
CG4	Major rutting, poor embankment surface protection, major wearing of crest elevation	0.20–0.40	Normal
CG5	Major rutting, very poor embankment surface protection, major wearing of crest elevation	0.40 +	Lognormal

Table 2
Seepage length loss in earth dykes and the assumed distribution for each condition grade.

Condition grade (CG)	Damage description	Loss of seepage length (m)	Distribution assumed
CG1	Cosmetic defects, very good soil condition, no vermin holes, slight width loss	0.00–0.05	Lognormal
CG2	Good soil condition, slight (rat size) holes in slope, slight width loss	0.05–0.15	Normal
CG3	Fair soil condition, minor (rabbit size) holes in slope, minor width loss	0.15–0.30	Normal
CG4	Poor soil condition, major (fox size) holes in slope, major width loss	0.30–0.60	Normal
CG5	Very poor soil condition, major (fox size) holes in slope, major width loss	0.60 +	Lognormal

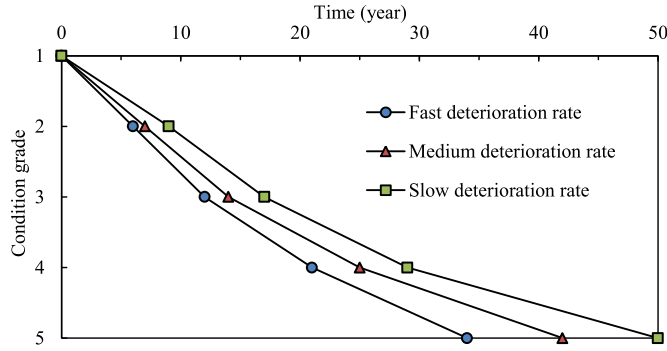


Fig. 4. Deterioration curves with respect to condition grades for a typical earth dyke with various deterioration rates.

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & 0 & \dots & 0 \\ 0 & p_{22} & p_{23} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & \dots & \dots & p_{M-1,M-1} & p_{M-1,M} \\ 0 & 0 & \dots & 0 & p_{MM} \end{bmatrix} \quad (8)$$

Due to the time-dependency for the asset deterioration process in reality, semi-Markov process is adopted in this study. Semi-Markov process is a stochastic time-dependent process with waiting times in any given state as independently distributed random variables. It is assumed that the waiting time T_i in state i of the process can be modelled as a random variable with a Weibull distribution due to its versatility [11]. Depending on the values of the parameters, the Weibull distribution can be used to model a variety of life behaviours in life data analysis. The probability density function (PDF) $f_i(t)$ and survival function $S_i(t)$ in state i over time t is expressed [30], respectively, as

$$f_i(t; \lambda_i, \kappa_i) = \lambda_i \kappa_i (\lambda_i t)^{\kappa_i - 1} \exp[-(\lambda_i t)^{\kappa_i}] \quad (9)$$

$$S_i(t; \lambda_i, \kappa_i) = 1 - F_i(t; \lambda_i, \kappa_i) = \exp[-(\lambda_i t)^{\kappa_i}] \quad (10)$$

where λ_i and κ_i are scale and shape parameters of the Weibull distribution in state i , respectively, which can be estimated from historical field inspection data.

In order to obtain the transition probability matrix for the semi-Markov process, the waiting times $\{T_1, T_2, \dots, T_{M-1}\}$ in the corresponding states $i = \{1, 2, \dots, M-1\}$ are assumed to be random variables. Thus, $T_{1 \rightarrow i}$ is a random variable representing the sum of waiting times in states from 1 to i , taking the process to go from state 1 to state i [11]. If the deterioration process is in state i at time t , the conditional probability transiting to next state $i+1$ in the next time step Δt (typically one year) is expressed as

$$p_{i,i+1}(t) = \frac{f_{1 \rightarrow i}(t) \Delta t}{S_{1 \rightarrow i}(t) - S_{1 \rightarrow (i-1)}(t)} \quad (11)$$

where $f_{1 \rightarrow i}$ is the PDF of waiting time $T_{1 \rightarrow i}$ and $S_{1 \rightarrow i}$ and $S_{1 \rightarrow (i-1)}$ are the survival functions of waiting times $T_{1 \rightarrow i}$ and $T_{1 \rightarrow (i-1)}$, respectively. The conditional probabilities in Eq. (11) generate the time-dependent transition probability matrix for the semi-Markov process.

3.3. State distribution probability

From the deterioration curves of flood defence assets, as shown in Fig. 4, the scale and shape parameters of the Weibull distribution can be estimated for each condition grade. It is assumed that τ_i represents the time step (year) that the asset remains in condition state i with probability of $\bar{p}_i$ (e.g. $\tau_i = 6$ year and $\bar{p}_i = 50\%$ for fast deterioration rate from state 1 to state 2 shown in Fig. 4), expressed by Eq. (10) as

$$S_i(\tau_i) = \exp[-(\lambda_i \tau_i)^{\kappa_i}] = \bar{p}_i \quad (12)$$

Meanwhile, the survival function $S_i(t)$ of the Weibull distribution in state i over time t should be close to the probability p_i^t that the asset remains in the same condition state i over time t , and the difference between them is expressed as

$$E_w = \sum_{t=1}^{\tau_i} |S_i(t) - p_i^t|^2 \quad (13)$$

where $p_i = \hat{p}_i^{1/\tau_i}$ represents the single step probability in state i after uniform transition with expected waiting time τ_i , and $\hat{p}_i$ is the probability that the asset remains in the same condition state i at time τ_i (e.g. at $\tau_i = 6$ year, assume $\hat{p}_i = 10\%$ for fast deterioration rate from state 1 to state 2 shown in Fig. 4). Thus, the scale parameter λ_i and shape parameter κ_i of the Weibull distribution in any state i are determined by solving the minimisation problem, defined as

$$\begin{aligned} \text{Min}(E_w) &= \text{Min} \sum_{t=1}^{\tau_i} \left| \exp[-(\lambda_i t)^{\kappa_i}] - \hat{p}_i^{t/\tau_i} \right|^2 \\ \text{Subject to: } &\exp[-(\lambda_i \tau_i)^{\kappa_i}] = \bar{p}_i \end{aligned} \quad (14)$$

After the Weibull distribution in any state i is obtained, the transition probability matrix for the semi-Markov process in any state i can be determined from Eq. (11). In the Markov process, the state of the process is often stochastic and can be defined by a probability mass function. The future state of the process at time $(T_{1 \rightarrow i} + n)$ in state i is then determined by

$$\mathbf{c}(T_{1 \rightarrow i} + n) = \mathbf{c}(T_{1 \rightarrow i}) \mathbf{P}_i^n \quad (15)$$

where $\mathbf{P}_i$ is the transition probability matrix in state i , and n is time in state i after waiting $T_{1 \rightarrow i}$ from state 1 to state i .

4. Time-dependent reliability analysis

The safety and reliability of coastal flood defences such as earth sea dykes during service time depend largely on operating environments such as hydraulic loading conditions and structural capacity. Climate change has the potential to impact condition and reliability of coastal flood defences, including increase in wave overtopping and increase in the rate of material degradation such as piping [31]. Sea level rise due to climate change reduces the depth-limiting effect of near-shore waves, which in turn leads to increased overtopping and the potential for larger wave impact forces. Larger waves drive progressive erosion and piping of the embankment or foundation soils. Therefore, the rise of sea level affects hydraulic loads acting on the coastal defences, which decreases the reliability of the structures. In the meantime, the resistance of the earth sea dykes deteriorates with time due to many factors, e.g. dyke crest level loss and seepage length reduction.

According to the failure statistics for earth embankment dams by

Foster et al. [32], wave overtopping and soil piping are two main factors causing structure failures, 46% all failures due to overtopping and 48% due to piping. Thus, these two typical failure mechanisms of earth sea dykes are considered for time-dependent reliability analyses, i.e. wave overtopping through the dyke crest and piping in the water conductive layer underneath the dykes. From the time-dependent reliability analysis, the quantitative risk of the earth sea dykes is estimated, which can then be used for optimising inspection and maintenance strategy.

4.1. Wave overtopping failure

Excessive wave overtopping discharge causes erosion of landside slope and weakens soil shear strength of earth sea dykes due to saturation of slope soils.

The overtopping rate of an existing sea defence mainly depends on its crest freeboard, defined as the height of the structure crest above still water level. The future crest freeboard over time $R_c(t)$ will be reduced due to sea level rise $\Delta h(t)$ and crest level loss $\Delta H_d(t)$ over time, expressed as

$$R_c(t) = R_c(0) - \Delta h(t) - \Delta H_d(t) \quad (16)$$

where $R_c(0)$ is freeboard at initial time. The crest level loss in state i is estimated from the condition state distribution $c_i(t)$ in state i , given in Eq. (15), and the corresponding vertical dyke crest level loss Δh_i . Then, the crest level loss $\Delta H_d(t)$ over time t is calculated from the sum of loss for all states ranging from 1 to M , written here as

$$\Delta H_d(t) = \sum_{i=1}^M c_i(t) \Delta h_i \quad (17)$$

The vertical dyke crest level loss Δh_i in any state i is evaluated from the data shown in Table 1. Here, the crest level loss is assumed to have a lognormal PDF for condition grades CG1 and CG5, and a normal PDF for the remaining condition grades CG2, CG3 and CG4. The mean values of the PDFs are taken as the average of the upper and lower limits of the crest height loss listed in Table 1. The standard deviation is estimated from the accuracy and confidence level of the field inspection data. For example, for inspections by experts, a value of approximately 90% may be used for the cumulative probability between two limits in determining the standard deviation. The PDFs of the earth dyke crest level loss for various condition grades are shown in Fig. 5. Thus, the vertical dyke crest level loss in any state can be estimated from the associated PDF using Monte Carlo simulations.

In addition to losing dyke crest height with time, rising sea level will reduce the future crest freeboard and also increase the future local significant wave height $H_{m0}(t)$. This will lead to significant increase in wave overtopping discharge. Continuing occurrence of excessive wave overtopping may cause failure of the landside slope of the earth dyke due to deterioration of soil strength. Here, failure caused by wave overtopping over time is defined as the exceedance of a predefined

mean overtopping discharge q_{cr} , and the limit state equation for overtopping failure is expressed as

$$Z_q(t) = q_{cr} - \chi_q q(t) \quad (18)$$

where χ_q is model uncertainty coefficient associated with overtopping parameters such as wave period, water depth and slope angle of fore-shore; and $q(t)$ is mean overtopping discharge with time, estimated in [23] as

$$\frac{q(t)}{\sqrt{gH_{m0}^3(t)}} = \frac{B_1}{\sqrt{\tan \alpha}} \gamma_b \xi_{m-1,0}(t) \exp \left[- \left(B_2 \frac{R_c(t)}{\gamma_b \gamma_f \gamma_\beta \xi_{m-1,0}(t) H_{m0}(t)} \right)^{1.3} \right] \quad (19)$$

with a maximum of

$$\frac{q(t)}{\sqrt{gH_{m0}^3(t)}} = B_3 \exp \left[- \left(B_4 \frac{R_c(t)}{\gamma_f \gamma_\beta H_{m0}(t)} \right)^{1.3} \right] \quad (20)$$

where $B_1 = 0.023$, $B_2 = 2.7$, $B_3 = 0.090$ and $B_4 = 1.5$ are empirical coefficients; γ_b , γ_f and γ_β are correction factors for berm, roughness and oblique wave attack, respectively; and $\xi_{m-1,0}(t)$ is local breaker parameter over time related to the slope steepness $\tan \alpha_1$, as shown in Fig. 1, defined as

$$\xi_{m-1,0}(t) = \frac{\tan \alpha_1}{\sqrt{H_{m0}(t)/L_{m-1,0}}} \quad (21)$$

in which $L_{m-1,0} = gT_{m-1,0}^2/2\pi$ is deep water wave length and $T_{m-1,0}$ is the mean energy wave period.

4.2. Soil piping failure

Ground water seepage in the water conductive soils such as sand underneath the earth sea dyke, as shown in Fig. 1, carries soil particles from the permeable layer due to water head difference. If this process continues long enough, pipes generate gradually in the water conductive soils, eventually causing collapse of the structure. The structure fails as a consequence of piping, if the water pressure head across the structure exceeds the critical head difference $h_{crp}(t)$ over time. The limit state equation for soil piping failure in [33] is rewritten here as

$$Z_p(t) = \chi_p h_{crp}(t) - h_p(t) \quad (22)$$

where χ_p is model uncertainty coefficient associated with soil piping parameters such as soil properties and seepage length; and $h_p(t)$ is the difference between sea water level at time t and water level at landside toe h_b , expressed as

$$h_p(t) = h(t) - h_b \quad (23)$$

The time-dependent critical head difference $h_{crp}(t)$ indicates the resistance of seepage in water conductive soils over time. The resistance of seepage deteriorates with time due to internal erosion and external holes in weakening soils, which can be represented by reducing seepage length over time [16]. The loss of seepage length in state i is estimated from the condition state distribution $c_i(t)$ in state i , given in Eq. (15), and the corresponding seepage length loss Δl_i . The reduction of seepage length $\Delta L_d(t)$ at time t is then calculated from the sum of loss for all states ranging from 1 to M , written here as

$$\Delta L_d(t) = \sum_{i=1}^M c_i(t) \Delta l_i \quad (24)$$

The seepage length loss Δl_i in any state i is simulated by Monte Carlo simulations on the basis of the assumed distributions given in Table 2. Similar to the dyke crest level loss, the seepage length loss is assumed to have a representative PDF for each condition grade. Again, the mean and standard deviation of the assumed distribution for each condition state are estimated from the seepage length loss range and data accuracy

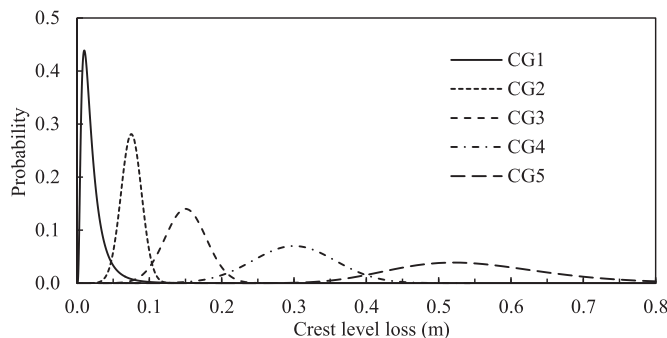


Fig. 5. Assumed probability density functions (PDF) of the earth dyke crest level loss for various condition grades (CG).

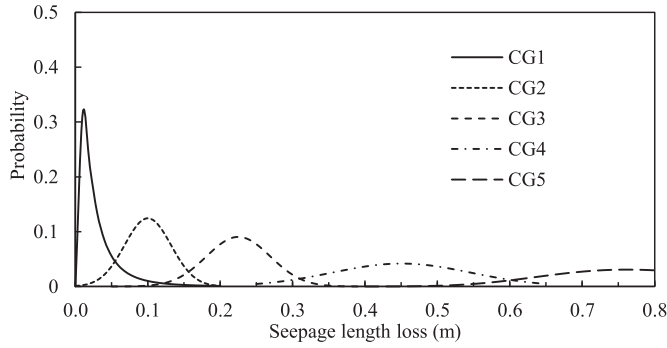


Fig. 6. Assumed probability density functions (PDF) of the earth dyke seepage length loss for various condition grades (CG).

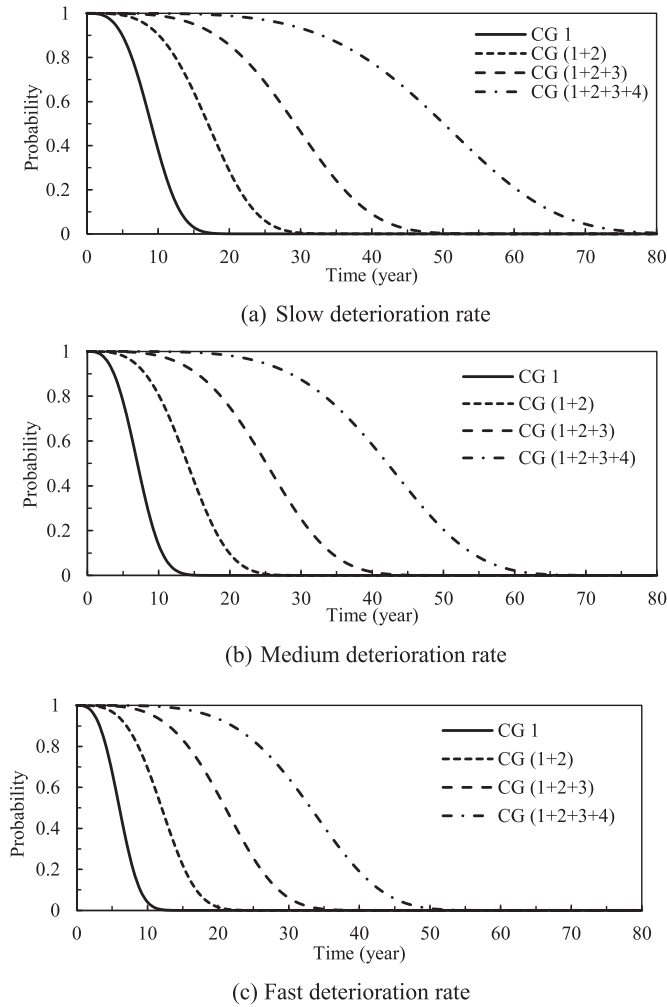


Fig. 7. Survival functions of cumulative waiting times for different condition grades (CG) subject to various deterioration rates.

level. The PDFs of the earth dyke seepage length loss associated with condition grades are shown in Fig. 6. Thus, the seepage length at time t is estimated from

$$L_p(t) = L_p(0) - \Delta L_d(t) \quad (25)$$

where $L_p(0)$ is initial seepage length. By modifying the formula given in [34] with consideration of seepage length deterioration over time, the time-dependent critical head difference $h_{crp}(t)$ is rewritten here as

$$h_{crp}(t) = \beta C_s \left(\frac{\gamma_s}{\gamma_w} - 1 \right) \tan \theta_s (0.68 - 0.10 \ln C_s) L_p(t) \quad (26)$$

where γ_s and γ_w are densities of water and saturated sand soils, respectively; θ_s is soil friction angle; factor β represents the effect of a finite thickness and coefficient C_s indicates the characteristics of soils during erosion, expressed respectively as

$$\beta = \left(\frac{D_s}{L_p} \right)^{\frac{0.28}{\left(\frac{D_s}{L_p} \right)^{2.8} - 1}}, \quad C_s = \omega d_{70} \left(\frac{1}{\varepsilon L_p} \right)^{\frac{1}{3}} \quad (27)$$

where D_s is thickness of sand layer; ω is drag force factor; d_{70} is representative of the fraction of large grains in the soils; and ε is intrinsic permeability.

4.3. Maintenance by multi-objective optimisation

During the life cycle of coastal flood defences, inspections and maintenance are often required to maintain the structures in an acceptable performance level. The maintenance actions therefore should be optimised to balance the risk of structure failures and the costs for maintenance during the service life. The risk of structural failures represents the probability of failures associated with failure modes such as wave overtopping and soil piping for the earth sea dykes. Due to the complexity in the limit state equations for wave overtopping failure and soil piping failure, the probability of failure is often evaluated using Monte Carlo simulation methods. Here, the inverse transform method is used for generating random variates, and the probability of failure is estimated from the number of failures generated [19]. Sufficient sample size is needed in the simulations to provide good estimates of failure probability.

Once the probability of failure over time is obtained, the annual probability of failure due to wave overtopping and soil piping at the n th year is calculated from

$$p(n) = p_f(t_n) - p_f(t_{n-1}) \quad (28)$$

The consequences of the dyke failure caused by wave overtopping and soil piping depend on the importance of the structure and the protected assets. The annual risk in monetary term caused by structural failures is expressed in [35] as

$$C_R(t) = p(t) C_{tot}(t) \quad (29)$$

where $C_R(t)$ is the expected value of loss due to the failure of the coastal flood defence; $p(t)$ is the annual probability of failure at time t ; and $C_{tot}(t)$ is total cost of loss at time t , determined by the sum of three different losses due to the structural failure, namely

$$C_{tot}(t) = \frac{1}{(1+r)^t} (C_{hazard} + C_{direct} + C_{erosion}) \quad (30)$$

where C_{hazard} is the direct hazard of injury or death to people immediately behind the defence; C_{direct} is the damage to property and infrastructure in the area defended; $C_{erosion}$ is the damage to the environment and erosion of the coastline; and r is the annual discount rate.

During the service life of coastal flood defences subjected to performance deterioration, a series of inspection and maintenance actions are needed. However, the observation and inspection of the structural condition of the flood defence assets using traditional methods such as visual inspection may contain uncertainties and errors. In order to model inspection error and the inability of capturing the condition grade of the assets, partially observable Markov decision process was proposed by introducing the observation matrix [36]. The value of information $V_I(t)$ over time t is employed for the cost needed to obtain information and the cost of making decisions on the basis of imperfect information, defined here as

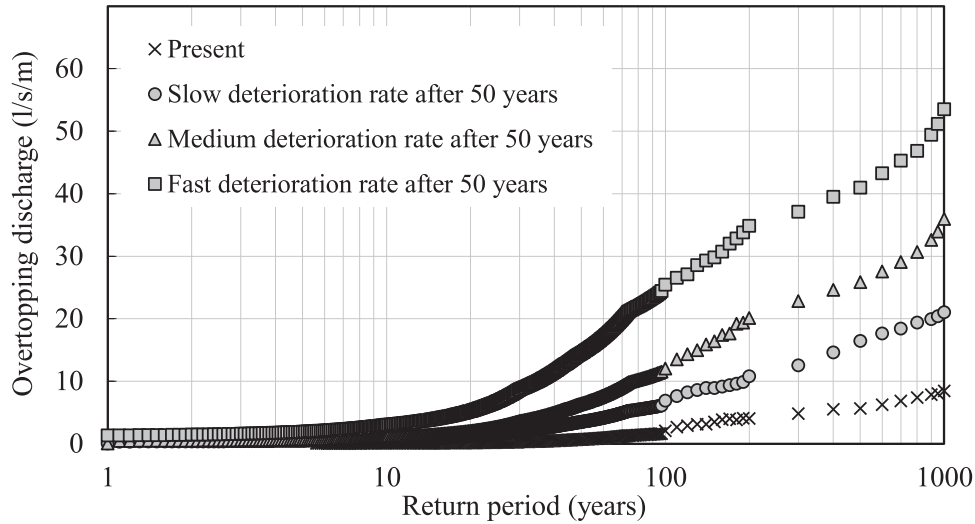


Fig. 8. Mean wave overtopping discharge (l/s/m) as a function of the return period of water level with various dyke crest level deterioration rates after 50 years.

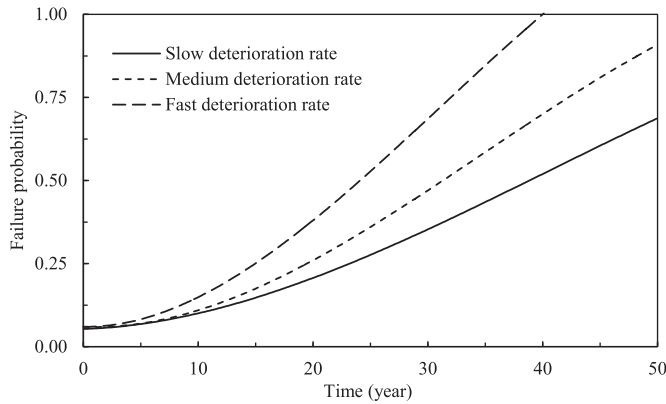


Fig. 9. Probability of failure of the sea dyke due to wave overtopping subject to various deterioration rates.

$$V_i(t) = C_{inspect}(t) + \mathbf{c}_{fail} \mathbf{P}(t)(\mathbf{O} - \mathbf{I})\mathbf{g} \quad (31)$$

where $C_{inspect}(t)$ represents the cost of conducting the condition assessment over time t ; $\mathbf{c}_{fail}$ represents the row vector containing the costs of failures and reduced level of service at different condition grades; $\mathbf{P}(t)$ is the transition probability matrix over time t ; $\mathbf{O}$ is the observation matrix measuring the reliability of the condition assessment activities; $\mathbf{I}$ is the identity matrix; and $\mathbf{g}$ is the column vector containing condition state indicators.

The planned inspection and maintenance strategy need to be scheduled and optimised to minimise the resources required as well as the risk due to structural failures. The primary goal of the optimisation is to allocate minimum cost for reducing the risk caused by unexpected structural failures. Thus, two main objectives should be achieved in the asset maintenance optimisation problem: 1) to minimise the cost of condition assessment strategy to be applied with optimised interval, and 2) to minimise the consequence of risk due to structural failure, expressed as

$$\text{Objectives: } \min[C_R(t)] \text{ and } \min[V_i(t)]$$

$$\text{Subject to: } t_{min} \leq t_I \leq t_{max} \quad (32)$$

where t_I is time interval between the minimum allowable time t_{min} and maximum allowable time t_{max} for the condition assessments. The optimisation toolbox based on genetic algorithm (GA) provided in MATLAB [37,38] is adopted to solve the multi-objective optimisation problem.

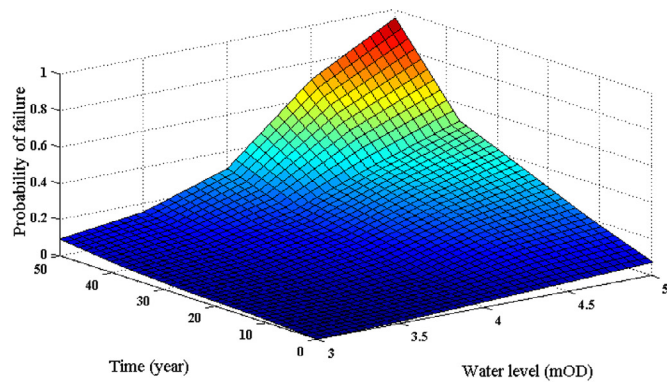
5. Numerical example

A numerical example for the simplified section of typical earth sea dykes along Allhallows-on-Sea at Thames Estuary [21], as shown in Fig. 1, is utilised for evaluating time-dependent reliability and optimum maintenance strategy. The dyke has a crest height of 6.60 mAOD, a seaside slope of $\text{Cot}(\alpha_1) = 3.20$ and a landside slope of $\text{Cot}(\alpha_2) = 2.80$. The seaside slope is protected by a berm and coarse gravels to reduce the destructive effects of the sea waves. The return periods of the hydraulic variables such as sea water level and significant wave height at the present condition are provided in Fig. 2. Due to sea level rise over time, the changes of water level and local significant wave height from the present day are shown in Fig. 3.

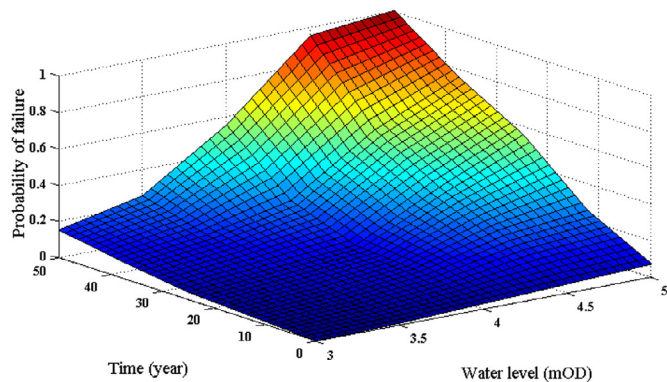
The earth sea dyke is assumed to be in a very good condition (CG1) at initial time. Three different deterioration curves with respect to condition grades for a typical earth sea dyke subject to various deterioration rates [28] are adopted, as shown in Fig. 4. These deterioration curves are then utilised to estimate the scale parameter λ_i and shape parameter κ_i of the Weibull distribution in each state i , by minimising the problem defined in Eq. (14). The trust-region algorithm is utilised to solve the minimisation problem, and the sum of squared errors is used to test the goodness-of-fit. The maximum sum of squared errors for the estimated scale and shape parameters is 4.42×10^{-4} , which confirms the suitability of the fitted model.

In order to simulate the dyke crest level loss and seepage length loss in any state, the assumed PDFs associated with different condition grades are utilised, as shown in Fig. 5 and Fig. 6, respectively. The distributions of the loss are assumed to be lognormal for condition grades 1 and 5, while normal distribution is assigned for condition grades 2, 3 and 4. The standard deviations of the distributions are estimated from the accuracy level of inspection data. For example, in the case for the dyke crest level loss in condition grade CG3 shown in Fig. 5, the mean value for the probability distribution is 15.0 cm. The standard deviation is estimated as 2.85 cm by assuming the inspection accuracy of 92%, i.e. 8% of all observed values belong to other condition grades.

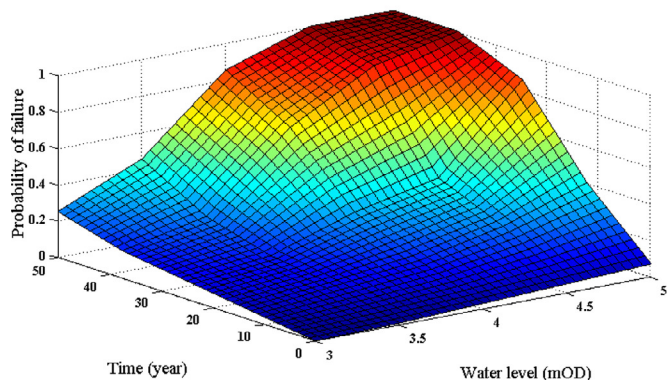
The estimated scale and shape parameters of the Weibull distributions are now utilised to calculate the cumulative survival distributions of the transition process between the condition grades. Fig. 7 shows the results for the obtained survival functions of cumulative waiting times for different condition grades for the dyke subject to various deterioration rates, i.e. slow, medium and fast deterioration rates. The results demonstrate how the rate of the earth dyke deterioration affects the survival probability in different condition grades. The survival functions of condition grade CG(1 + 2 + 3 + 4) represent the sum of



(a) Slow deterioration rate



(b) Medium deterioration rate



(c) Fast deterioration rate

Fig. 10. Time-dependent fragility surfaces associated with wave overtopping failure subject to various deterioration rates.

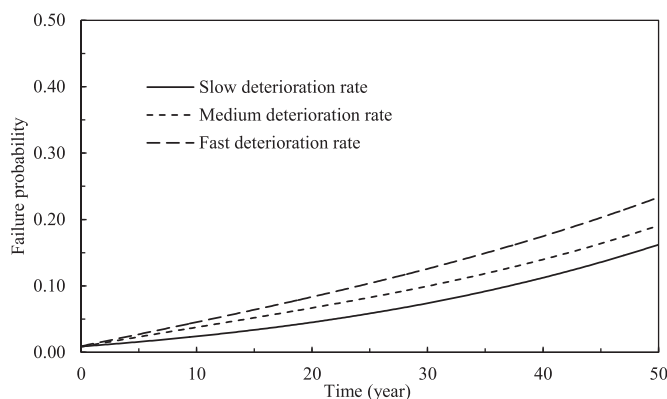
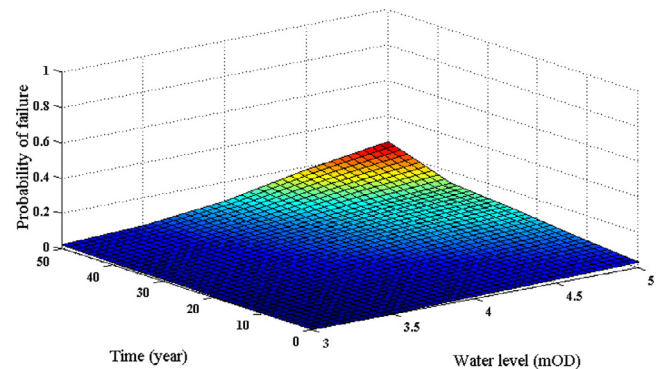
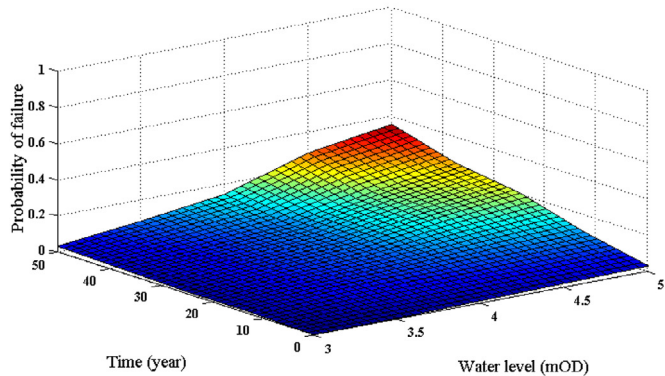


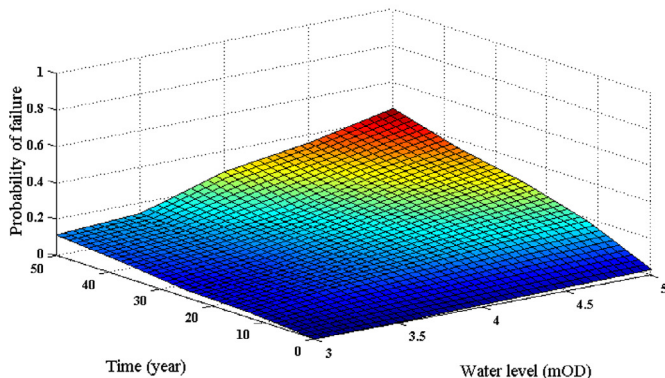
Fig. 11. Probability of failure of the earth sea dyke due to piping in soils subject to various deterioration rates.



(a) Slow deterioration rate



(b) Medium deterioration rate



(c) Fast deterioration rate

Fig. 12. Time-dependent fragility surfaces associated with soil piping failure subject to various deterioration rates.

values from CG1 to CG4, and indicate the survival probability of asset age at failure, giving the expected lifetimes of 50, 42 and 34 years at the survival probability of 50% for slow, medium and fast deterioration rates, respectively. This is consistent with the expected lifetimes for different deterioration rates shown in Fig. 4. When the dyke deterioration rate increases, the survival probability in certain condition grade decreases, and the cumulative waiting time also decreases.

The time-dependent transition probabilities $p_{i,i+1}(t)$ are now generated using Eq. (11), on the basis of the estimated PDFs and survival functions of waiting time. Once these transition probabilities for the semi-Markov process in any state are obtained, the future state distributions of the process can be determined from Eq. (15). The predicted future state distributions are then used for estimating the dyke crest level loss over time related to wave overtopping failure and the seepage length loss over time related to soil piping failure. Consequently, time-dependent probability of failures associated with wave overtopping and soil piping of the earth sea dyke can be estimated by

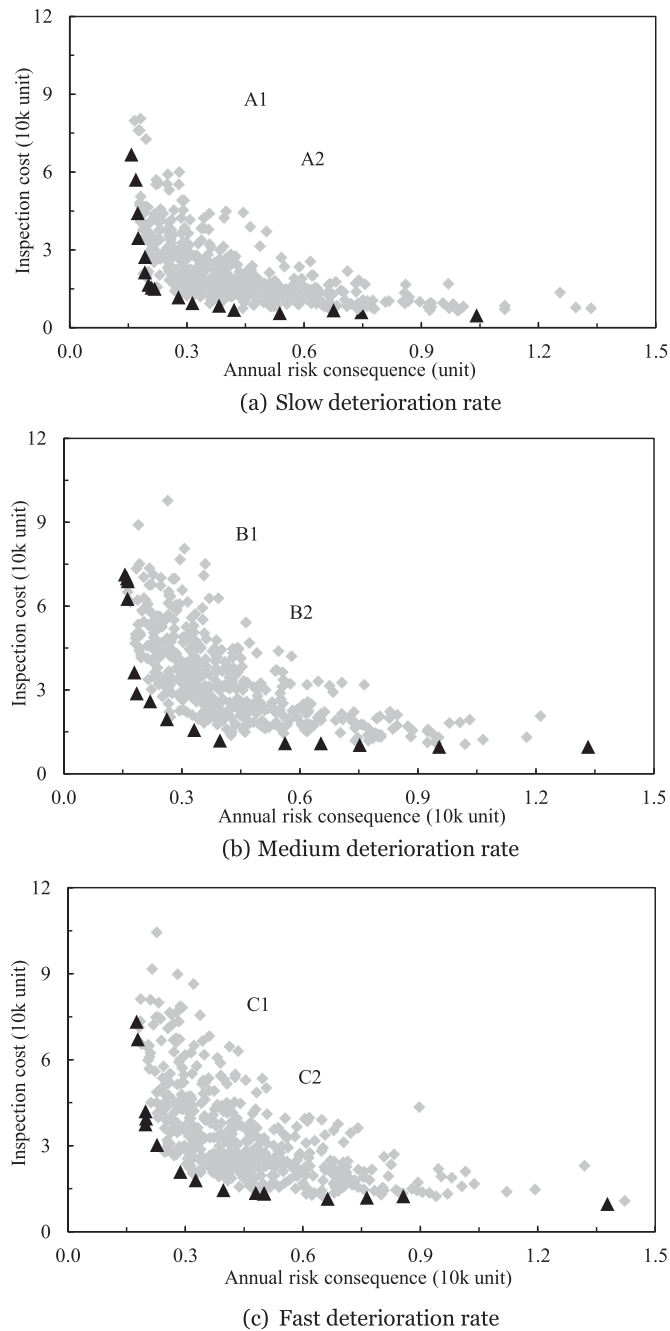


Fig. 13. Optimum solution sets for inspection strategy of the earth sea dyke subject to various deterioration rates.

Table 3

Optimum maintenance solution samples from the multi-objective optimisation.

Pareto solution	Deterioration rate	Expected risk consequence (unit)	Total cost of inspection (unit)	Tier 1 time interval	Tier 3 time interval
A1	Slow	1753	34,618	2	5
A2	Slow	4207	6903	5	11
B1	Medium	1792	36,304	2	4
B2	Medium	3968	11,935	3	7
C1	Fast	2275	30,281	2	5
C2	Fast	3970	14,523	3	7

taking into account both changing hydraulic variables and deteriorating structural capacities.

Fig. 8 shows results for the mean wave overtopping discharge with respect to the return period of water level, where the dyke crest level deteriorates after 50 years from the present day at various deterioration rates. The correction factors for berm γ_b and roughness γ_f are taken as 0.65 and 0.80, respectively. The wave overtopping discharge depends largely on the hydraulic variables associated with a certain return period and the dyke crest freeboard. The overtopping discharge increases significantly when the dyke crest level deterioration rate increases. In the case for the 1000-year return period event, the mean overtopping discharge after 50 years will increase to approximately 2.8, 4.6 and 6.8 times of the present discharge for the dyke subjected to slow, medium and fast deterioration rates, respectively.

Time-dependent reliability analysis is carried out for wave overtopping through the earth dyke crest. Here, a critical wave overtopping discharge of 2 l/s per metre, suggested by CIRIA [39] for protecting earth dyke crest and landside slope, is adopted in the limit state equation for the wave overtopping failure. A total number of 10^5 samples is utilised in the Monte Carlo simulations to estimate the probability of failure. The results in Fig. 9 show the probability of failure caused by wave overtopping against time during the period of 50 years after the present day, where a local water level of 4.50 MOD at the present day is considered. Both sea level rise and dyke crest level loss are considered in the calculations. From the results, the probability of failure due to overtopping depends heavily on the rising sea level and deteriorating dyke crest level, and increases significantly with time. The probability of failure for the earth sea dyke subjected to fast deterioration rate after 30 years is about 21% and 34% higher than those for medium and slow deterioration rates, respectively. This indicates obviously the influence of dyke crest level loss on wave overtopping failure, since they have the same sea level rise during the period concerned.

Fig. 10 shows the results for time-dependent fragility surfaces associated with wave overtopping through the dyke crest subject to various deterioration rates. From the results, the probability of overtopping failure is not only related to water level in traditional fragility curves, also depends on the age of the earth sea dyke. As age progresses, the dyke will be subjected to both more severe hydraulic loading conditions including sea level rise and the crest level loss over time. For slow deterioration rate, the probability of overtopping failure reaches approximately 50% in the cases with asset age of 40 years and water level at 4.5 MOD or asset age of 34 years and water level at 5.0 MOD. For fast deterioration rate, the probability of overtopping failure increases significantly and gives the same value in the cases with asset age of 40 years and water level at 3.7 MOD or asset age of 15 years and water level at 5.0 MOD.

The piping failure mechanism is associated with both the increase in water pressure head between the water levels at the seaside and land side and the deterioration of seepage resistance in the underlying water conductive soils. The water level on the seaside increases due to rising sea level, and the water level on the land side is assumed at ground level. To estimate the seepage length in the water conductive sand layer, soil parameters are assumed to have the saturated density $\gamma_s = 17 \text{ kN/m}^3$, soil friction angle $\theta_s = 35^\circ$, intrinsic permeability $\varepsilon = 1.28 \times 10^{-10} \text{ m}^2$, drag force factor $\omega = 0.25$, and large grain fraction $d_{70} = 0.3 \text{ mm}$. The seepage length loss with time is then simulated using the assumed probability distributions shown in Fig. 5 for various deterioration rates.

The results for the probability of soil piping failure of the earth sea dyke subjected to various deterioration rates are plotted in Fig. 11, where the local water level of 4.5 MOD is considered. The probability of piping failure increases steadily with time due to sea level rise and seepage length loss in soils. As expected, the dyke deterioration rate has influence on the probability of failure of the earth dyke, with a value of approximately 7.5% for slow deterioration rate and an increased value

of approximately 13% for fast deterioration rate. The results show that soil piping has lower values of probability of failure in comparison with wave overtopping, however, the consequence of piping failure in soils is much more severe.

Fig. 12 provides the results for time-dependent fragility surfaces associated with piping in underlying water conductive soils subject to various deterioration rates. The probability of soil piping failure is expressed here as functions of water level and asset age due to double effect of sea level rise and soil seepage length deterioration over time. Here again, the probability of piping failure increases significantly with water level and asset age. The probability of failure reaches approximately 10% in the condition of water level of 4.5 mOD and asset age of 37 years for slow deterioration rate, but the asset ages reduce to 29 and 23 years for medium and fast deterioration rates, respectively. Soil piping in the water conductive layer will pose more serious risk over time to the earth sea dyke when the dyke deteriorates faster.

In order to reduce the risk of structural failure, a multi-objective optimisation method is adopted to minimise the consequence of the annual risk while requiring minimum inspection costs, as defined in Eq. (32). Reasonable data are assumed in this example due to lack of inspection and failure costs for the earth sea dyke. Actual data should be adopted in evaluating optimum inspection and maintenance strategy in practice. In calculating the annual failure risk, the total cost of loss is the sum of hazard cost $C_{\text{hazard}} = 7,000$ units, direct property damage cost $C_{\text{direct}} = 4,500$ units, and environment and erosion damage cost $C_{\text{erosion}} = 600$ units. Unit in this example represents a certain currency value, since only relative costs are required in this optimisation problem. To estimate the value of information, a yearly time interval for possible inspection is used, and the available inspection strategies include Tier 1 inspection such as visual inspection with cost of 30 units and Tier 3 inspection such as detailed survey with cost of 120 units. The observation matrices reflecting the accuracy of inspection strategies are assumed to have values of 80% for Tier 1 inspection and 92% for Tier 3 inspection for each condition grade. The genetic algorithm is adopted to solve the multi-objective optimisation problem, with chosen parameters including probability of mutation of 0.1, probability of crossover of 0.4 and population size of 600. The upper and lower bounds for the time interval between inspections are taken as $t_{\text{min}} = 3$ years and $t_{\text{max}} = 12$ years.

Fig. 13 shows the results for optimum solution sets related to annual failure risk consequence and total inspection cost of the earth sea dyke subjected to various deterioration rates. It is obvious that the dyke deterioration rate has influence on optimum inspection strategy, and the annual risk consequence and total inspection cost will increase generally when the deterioration rate becomes higher. From the results, there are some dominated solutions for different deterioration rates with the balance between the annual risk consequence and total inspection cost. The solution sets allow a decision maker to choose the best choices based on available resources and the risk of asset failures.

Table 3 provides samples of the optimum solutions over the solution space for the multi-objective optimisation problem. The results show the expected annual risk consequence, total cost required for inspections, and time interval for different condition assessment strategies of the earth sea dyke subjected to various deterioration rates. Each solution dominates the optimal space in one objective, e.g. total inspection cost or annual risk consequence. For example, in the case for slow deterioration rate, solution A1 has an expected annual risk consequence of 1753 units, which is lower than solution A2 of 4207 units. However, solution A2 costs much less than solution A1 in terms of overall inspection cost, reducing from 34618 units for solution A1 to 6903 units for solution A2. Thus, solution A2 may be preferred with relatively longer inspection intervals, when the budget for the asset management is limited.

6. Conclusion

This paper presents an approach for undertaking time-dependent reliability analysis and providing quantitative risk assessment of coastal flood defences with consideration of both changing hydraulic conditions and deteriorating structural capacity over time. The impact of climate change on the local hydraulic variables such as water level and significant wave height is investigated. Meanwhile, the deterioration of the structural resistance of the earth sea dyke such as the dyke crest level loss and soil seepage length reduction is modelled using the semi-Markov stochastic process. The future condition of the dyke is then predicted from the estimated non-homogeneous transition probability matrix. The time-dependent probability of failure associated with wave overtopping through the dyke crest and piping in water conductive soils is estimated by taking into account both changing hydraulic variables and deteriorating structural resistance. The results obtained from the reliability analysis are then employed to evaluate optimum inspection and maintenance solutions using a multi-objective optimisation method. Finally, a numerical example for a typical section of the earth sea dyke at Thames Estuary is utilised to demonstrate the applicability of the proposed approach.

From the results for the numerical example, the following conclusions are noted: 1) The future hydraulic variables acting on the coastal flood defence become more severe due to sea level rise, and the local significant wave height increases with time as a result of rising sea level; 2) The field inspection data together with the deterioration curves by expert judgements provide a useful basis for probabilistic deterioration modelling and quantitative risk assessment of aging dykes; 3) The probability of failure associated with wave overtopping and soil piping will increase significantly with time due to double effect of increasing hydraulic loading caused by rising sea level and reducing structural capacity caused by asset deterioration, leading to higher annual failure risk; 4) The multi-objective optimised solution space by minimising annual risk consequence and total inspection costs provides asset managers with better solution choices to manage the deteriorating coastal flood defences with limited resources available. The intervention policy such as repair planning will be considered in the multi-objectives in the future research on optimising maintenance strategy of coastal flood defences.

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